# DEVELOPING PRIORITY INDEX FOR MANAGING UTILITY DISRUPTIONS IN URBAN AREAS WITH FOCUS ON CASCADING AND INTERDEPENDENT EFFECTS

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**ABSTRACT**

Unanticipated events such as natural disasters, terrorist attacks, cyber-attacks, etc. could cause prolonged disruptions in major utility service networks including water, electricity, etc., in urban areas. Due to the presence of complex interdependencies among infrastructure systems in an urban network, the disruption of one system may trigger a chain of events that degrade the proper functioning of several other dependent systems. Consequently, many parts of the city may not have access to multiple utility services and amenities. Identifying the most vulnerable communities exposed to such utility disruptions is key to performing immediate relief operations. In this paper, the concept of Priority Index, introduced as a measure of the susceptibility of communities to the event, has been presented to rank urban regions based on the extent of the impact of disruptions (both cascading and interdependent impacts) due to an event, as well as the social vulnerability of communities. Agent-based models are employed to simulate the consequences of a disruptive event on a semi-realistic urban infrastructure network. Later, the extent of impact on communities is evaluated using the simulation results and the American Community Survey data. The proposed Priority Index could help city administrations, as well as utility service agencies, identify the regions in a city that require immediate attention after a disruptive event occurs in the infrastructure network. A case study based on a semi-realistic infrastructure network in Austin, Texas is presented to demonstrate the implementation of the concept of Priority Index and the methodological framework.

*Keywords*: urban infrastructure, dependencies and interdependencies, emergency planning, communities, disasters

## INTRODUCTION

Human civilizations gave shape to cities, and technology made cities better. Today, cities constitute the most critical element of the social and economic development of nations. The two most important components of cities are its infrastructure network and its communities. The mutual dependence of these two components has resulted in efficient and constantly evolving cities. However, this integral nexus, while being an opportunity, is also a challenge for urban planners, because disturbances on either of these two components by any external incident will have far-reaching consequences in the other, and has the potential to bring a city to halt. Due to the networked structure of urban infrastructure systems, failure of a system could further trigger failure of dependent systems in the network, and consequently cause widespread disruptions in public utility services. This has been evident in many past incidents like World Trade Center attack in 2001, the Northeast blackout in 2003, the Indian Ocean earthquake in 2004, etc. These events were unforeseen, and their consequences on infrastructure systems were aggravated by the complex and interdependent structure of urban infrastructure network. Thus, during such disasters, urban communities are susceptible not only to the direct impacts of the disaster, but also to prolonged utility disruptions resulting from the inability of infrastructure systems to function at satisfactory performance levels. At present, there are vulnerability assessment tools to predict the direct impact of disasters on communities. However, there is a lack of models to evaluate the indirect impacts, such as large-scale utility disruptions. In this paper, the authors present a framework and modified measure called Priority Index (PI) to prioritize relief operations during emergencies that would simultaneously augment the infrastructure and community resilience of a city.

The rest of the paper is organized as follows: the Literature Review section presents a review of existing literature pertaining to this study; the Methodology section elaborates on the framework adopted for developing PI; the Case Study section presents the implementation of the methodological framework; and the Conclusion section lists the findings.

## LITERATURE REVIEW

The characteristics of a city are largely dependent on its infrastructure systems, such as utility services, economic institutions, and transportation infrastructure. Infrastructure systems are critical for ensuring an adequate supply of resources and services to communities, economic sectors, and other social institutions in a city. In addition, several studies in the past have validated the constructive role of urban infrastructure in stimulating the social and economic development of cities and nations. Some of the areas in which infrastructure development made significant improvements are economic development (*1*), poverty alleviation (*2*), social equity (*3*), and agricultural and regional development (*4*).

A modern urban infrastructure network can be considered as a complex and dynamic system of interconnected and interdependent infrastructures. Rinaldi (*5*) classified the interdependencies existing among infrastructure systems into four categories, namely, physical, geographic, cyber, and logical interdependencies. Physical interdependency is linked to material flows, whereas, cyber interdependency pertains to information flows. Geographic interdependency relates to physical proximity, and finally, logical interdependency encompasses all other types of interdependencies. In an interconnected network, the performance of an infrastructure system is influenced not only by its functional capability, but also by the performance of its dependee systems. Though the interdependent nature of urban infrastructure ensures operational efficiency of component systems, it can also increase system vulnerability (*6*). A disruptive event that affects an infrastructure

system could trigger cascading and interdependent effects on its dependent systems, degrading their functional efficiency. The ability of communities to endure such disruptions depends on their socio-economic characteristics. However, major social and economic disparities among urban communities are commonplace in cities. Hence, from an emergency management perspective, the disaster risks arising due to such interdependencies on infrastructure systems and communities needs to be assessed using an integrated approach. The first step in the process of evaluating the vulnerability in an infrastructure network is to quantify the consequences arising due to interdependencies.

## Methods for Quantifying Interdependent Effects of Hazards

Ouyang (*7*) identified and classified various methods for quantifying the interdependent effects in networked infrastructures into five categories, namely, empirical-, agent based-, system dynamics based-, economic theory based-, and network based approaches. In the empirical approach, the interdependencies are quantified based on historical failure patterns and expert experience (*8*). Agent-based models consider each component of a complex infrastructure network as an autonomous agent whose functions are decided by a set of well-described rules. This is a bottom-up approach which can be used to simulate the interdependent effects in large-scale urban systems (*9*). Studies like the one by Brown *et. al.* (*10*) used principles of system dynamics to evaluate the potential risks to critical systems arising from the interdependencies in infrastructure networks. Another important approach is the input-output inoperability model (IIM) derived from the Leontief Input-Output economic model used for assessing the stability of economic systems (*11*). This approach has been used in several hybrid models for evaluation of infrastructure interdependencies. Recent studies have focused more on models based on network theory (*12*). An infrastructure system can be treated as a graph, where nodes represent infrastructure components and links represent interdependent relationships.

## Methods for Evaluating Social Vulnerability to Hazards

The approaches summarized in the previous section have been used for evaluating the effect of interdependencies in aggravating the risks on infrastructure networks arising from unanticipated events. The authors also conducted another phase of the literature review to understand how hazard risks on urban communities are evaluated, and whether interdependent effects are considered in the evaluation.

Social vulnerability indicates how sensitive communities are to hazards, and their ability to respond during such events. The metrics to evaluate the vulnerability of communities to hazards can be broadly classified into two categories: generic vulnerability measures and event-specific vulnerability measures. The generic vulnerability measures use surrogate socio-economic, built-environment, and demographic variables to identify the most vulnerable communities. Cutter and Finch (*13*) constructed a Social Vulnerability Index (SoVI) for evaluating the social vulnerability of communities to environmental hazards. The researchers identified 42 relevant variables from US Census data to develop SoVI for the counties in the United States. In a similar effort, Flanagan *et. al.* (*14*) developed another generic social vulnerability index (SVI) for the Agency for Toxic Substances and Disease Registry using 15 census variables pertaining to socio-economic status, household characteristics, demographic characteristics, and housing characteristics. SVI is an ordinal measure which indicates the percentile rank of census tracts based on the variables.Though the index provides the vulnerability ranks of census tracts, relative comparisons about the mag-

nitude of vulnerability are not possible. Huang and London (*15*) developed a census block level social vulnerability index as a measure of the health challenges posed by hazards, based on six variables, namely, proximity to healthcare facilities, poverty rate, education, linguistic isolation, race/ethnicity, and age. The advantages of this index are that it is a normalized value between 0 and 1, and that it can be used for relative vulnerability comparisons.

Event- or hazard-specific social vulnerability measures, along with generic vulnerability factors, also account for the factors or policies that can augment the community's response to that particular hazard. For example, Chakraborty *et. al.* (*16*) combined generic vulnerability index and geophysical risk index (an index based on vulnerability to floods) to prioritize evacuation assistance needs in Florida. Schmidtlein *et. al.* (*17*) simulated the potential earthquake losses in South Carolina using the HAZUS-MH software (developed by the Federal Emergency Management Agency) and assessed the correlations with SoVI values. The study also identified the most significant census variables that are correlated with losses to earthquakes. Rygel *et. al.* (*18*) developed a social vulnerability indicator for assessing the impact of storm surges resulting from hurricanes. The researchers performed principal component analysis to identify the most relevant set of factors affecting vulnerability to the hazard under consideration.

The review revealed that literature is scarce when it comes to evaluating the vulnerability of communities to widespread utility service outages resulting from various types of hazards. 3. The direct impacts of disasters on communities, such as health hazards and physical harm, may be limited to the location of occurrence. However, the indirect impacts, such as prolonged utility service disruptions arising from infrastructure system failures during a disaster, are more likely to affect communities in other regions of cities, as well. This warrants the need for a framework to assess and prioritize communities who are most vulnerable to the indirect impacts of disasters resulting from the interdependent nature of infrastructure systems.

## METHODOLOGY

Figure 1 presents the methodological framework adopted for developing the Priority Index (PI). The index is designed to rank census tracts based on their vulnerability to utility disruptions resulting from an unanticipated event. The framework consists of two independent components. The first component is the quantification of the impacts of the event on the performance of various utility systems in the infrastructure network (from which a community's exposure to such disruptions can be quantified) using agent-based modeling (ABM) approach. The exposure would depend on the structure of the infrastructure network, and the interdependent relationships existing among its various components. The second component is the evaluation of the social vulnerability of communities residing in the affected regions from publicly available American Community Survey (ACS) data. Social vulnerability variables could be used as surrogate measures to evaluate the capability of communities in a census tract to endure prolonged utility disruptions. Once the exposure and social vulnerability are quantified, they are combined to develop the PI. In the rest of the section, the various stages in the development of PI are elaborated.

### Development of the Infrastructure Network and Defining Interdependencies

Every urban infrastructure network consists of numerous interconnected and interdependent infrastructure systems (or utility services) such as electricity grid, water supply system, sewage disposal system, and so on. Though each of these infrastructure systems are established independently, they depend on other infrastructure systems for their proper functioning. The degree of depen-

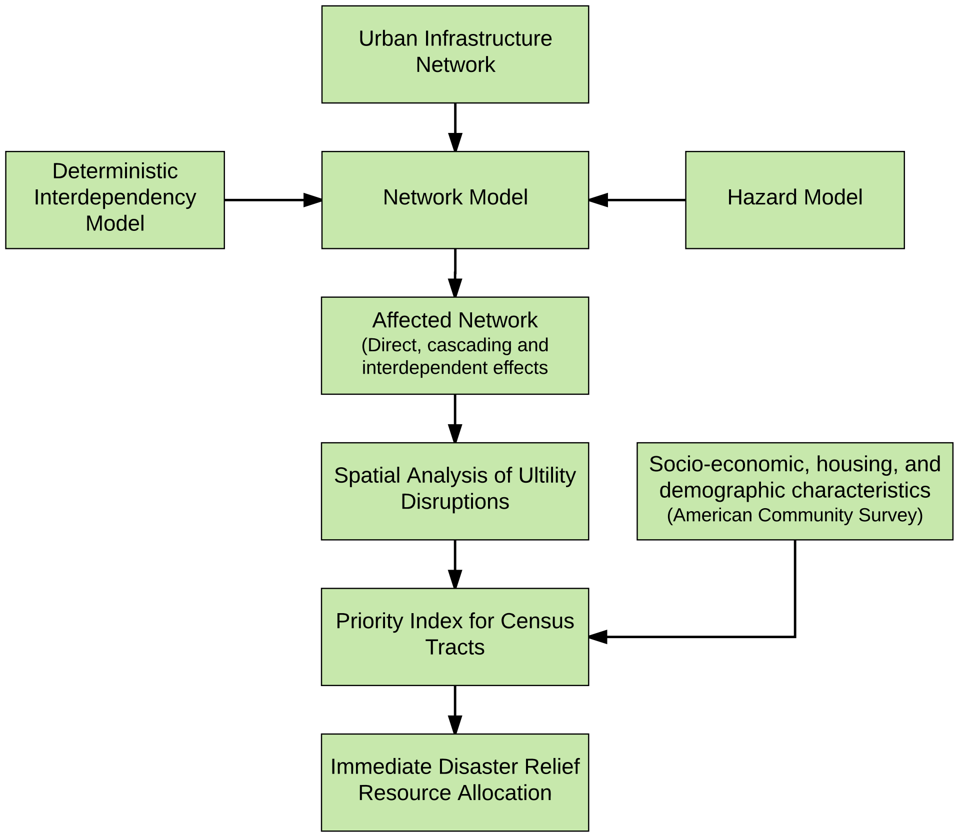


**FIGURE 1**: **Methodological Framework for Developing Priority Index**

dency of an infrastructure system on another is affected by various factors, including the resources and services required by the former, the resources and services produced by latter, geographical proximity, etc. Any degree of performance drop in one infrastructure node in the network could trigger further performance drops in its dependent nodes in the presence of such dependencies and or interdependencies. This may disrupt the normal supply of multiple utility services in the affected regions.

As mentioned before, the first stage in the process of developing PI is to analyze and estimate the network level performance drop in various utilities which might occur due to the disruptive event. Since the urban infrastructure network consists of several infrastructure systems which are composed of individual infrastructure units, it could be modeled as a graph over a geographical information system (GIS) framework. An infrastructure system can be regarded as a subgraph and individual infrastructure units as nodes. The dependencies could be modelled as unidirectional links in the graph, each of them carrying a weight according to the degree of interdependency. Mathematically, the network model can be represented as follows (Equation 1):

$$G_\Omega = (N_\Omega, D_\Omega), \tag{1}$$

where $G_\Omega$ is the infrastructure network model on a GIS framework $\Omega$, $N_\Omega$ is the set of infrastructure nodes, and $D_\Omega$ is the set of dependencies among the infrastructure nodes. Each of the nodes, $i \in N_\Omega$,

belongs to an infrastructure type, $K$, from a set $\kappa : \kappa(i) = K$. If a node $i$ is dependent on another node $j$, the dependency between the two nodes is represented as follows (Equation 2):

$$d_{ij} \in D_\Omega \iff \exists d_{ij} \tag{2}$$

Whether $i$ is connected to $j$ is dependent on their respective infrastructure types and the service area of $j$ . If there exists both $d_{ij}$ and $d_{ji}$, it is called an interdependency. Equations 1 and 2 define the structure of the infrastructure network model. However, the degree of dependencies among various nodes vary depending on the infrastructure types. The interdependency model $W$ is a set of dependency values in the range of [0, 1] mapped against every $d_{ij}$ that exists in the network. For the present study, a deterministic interdependency model is adopted. Mathematically,

$$w_{ij} \in W = w_{\kappa(i)\kappa(j)} \iff \exists d_{ij}, \tag{3}$$

where $w_{ij}$ is the dependency value of $i$ on $j$, $w_{\kappa(i)\kappa(j)}$, is the dependency value for infrastructure type $\kappa(i)$ dependent on $\kappa(j)$.

**Simulation of Disruptive Event and Evaluation of Post-Event Performance of Infrastructure Network**

Consider a disruptive event, $H$, occurring at a point $p(x,y)$, where $x$ and $y$ are the longitude and the latitude of the point $p$, respectively. The disruptive event affects a certain geographical region, $\omega \subset \Omega$. The event could be modeled as a function of initial intensity at $p, \iota_0$, time of occurrence, $T$, and the speed of propagation of impact, $\nu$, as follows:

$$H = f(\iota_0, T, \nu) \tag{4}$$

The impact of $H$ on node $i$ is dependent on initial intensity and distance of the node from the point of occurrence, and is given by Equation 5.

$$\iota_H^i = f(\iota_0, \ell ip) : 0 \leq \iota_H^i \leq 1, \tag{5}$$

where $\ell_{ip}$ is the distance between $i$ and $p$. If initial expected performance of $i$ at time $T$ is represented by $P_i(0) : 0 \leq P_i(0) \leq 1$, then the expected performance of $i$ after the occurrence of the event can be modeled using Equation 6.

$$P_i(T+\tau) = \begin{cases} P_i(0) & \text{if } \tau < \frac{\ell ip}{v} \\ P_i(0) - \iota_i^H & \text{if } \tau \geq \frac{\ell ip}{v} \end{cases}, \tag{6}$$

where $\tau$ is time elapsed after $T$ until the instance under consideration. Along with physical impact of an event on a node, the expected performance can also degrade due to the shortage of the supply of adequate resources on time. The latter becomes obvious if infrastructure systems in the network are interdependent. The reduction in expected performance of node $i$ will reflect in the expected performance of those nodes that are dependent on $i$ for their functioning. However, Equation 6 does not account for such interdependent and cascading effects of the event on the network. Accounting for this factor in the performance of nodes, the expected performance at any time $t$ can be simulated

using the following generalized expression:

$$P_i(t) = \max\left(0, P_i(t-\Delta t) - \left[\sum_j \left(1 - P_j(t-\Delta t)\right) w_{ij}\right] - \rho_i \iota_i^H\right) : 0 \leq P_i(t) \leq 1, \tag{7}$$

where $\Delta t$ is the simulation step size, $J$ is set of all dependee nodes of $i$, and $\rho$ is an indicator variable with value 1 if $t - T > \frac{\ell_{ip}}{v}$, and 0 otherwise. The expected performance loss in any node $i$, $1 - P_i(t)$ is the exposure of $i$ to the event $H$.

**Spatial Analysis of Hazard Exposure and Social Vulnerability of Communities**

Once the post-event expected performance of utility services is estimated, the analysis must identify how the disruptions affect the communities. For this purpose, the following steps are adopted:

1. Create an adequate sample of buildings that are dependent on the disrupted utility services based on the actual spatial distribution of building footprint in the study area.
2. Identify and map the dependent utility service nodes to each building in the sample and their corresponding post-event performance levels.
3. Identify and map the buildings to the corresponding census tract to which they belong.
4. Evaluate the distribution of utility service disruptions in each census tract from the building data. This provides information about the exposure of each census tract to the utility service disruptions resulting from the reduced performance levels of the infrastructure nodes.

Next, the generic social vulnerability characteristics of communities are analyzed. The underlying assumption is that those populations with higher social vulnerability to disasters are more likely to be affected than their counterparts with lower social vulnerability during a disaster or disruptive event. Data from censuses and related updates can be used to obtain relevant information about the demography, infrastructure, and socio-economic characteristics of communities residing in the city. In the United States, the Census Bureau conducts American Community Survey (ACS) to collect data regarding communities at various geographic levels every year. Based on the ACS data, the Agency for Toxic Substances and Disease Registry (*14*) has developed a Social Vulnerability Index (SVI) for each of the census tracts using 15 social factors that describe a community's social vulnerability (Table 1). However, the limitation of SVI is that it is an ordinal measure, and hence does not convey the magnitude of relative differences in vulnerability across regions. Hence, a modified Social Vulnerability Index (mSVI) is developed based on the same set of variables, which also accounts for the relative difference in social vulnerabilities. An approach like the one suggested by Huang and London (*15*) is adopted for developing mSVI.

Consider a census tract, $m$, with the social factors listed in Table 1 denoted by a set, $S$. The corresponding mSVI is given by Equation 8.

$$mSVI_m = \frac{\sum_{s \in S} s_m}{15 \times 100} \tag{8}$$

In order to convert $mSVI_m$ to its normalized form, Equation 9 is employed.

$$mSVI_{m,norm} = \frac{mSVI_m}{\max(mSVI_m)} : 0 \leq mSVI_{m,norm} \leq 1 \tag{9}$$

**TABLE 1**: **Social Factors Considered in Developing SVI (Agency for Toxic Substances and Disease Registry)**

| **Category** | **Variables** |
|---|---|
| Socio-economic status | • % of population below poverty<br>• % population unemployed<br>• per capita income[a]<br>• % population without high school diploma |
| Household composition & disability | • % population older than 65 years of age<br>• % population younger than 17 years of age<br>• % civilians with disability<br>• % single parent household |
| Minority status and language | • % population belonging to minority communities<br>• % population speaking English "less than well" |
| Housing and transportation | • % multi-units structures<br>• % mobile homes<br>• % housing units with more people than rooms<br>• % households with no vehicle<br>• % persons in institutionalized group quarters |

[a]During the calculation of mSVI, per capita income (pci) is converted into a percentage variable which is equivalent to the ratio of the difference between the highest tract-level pci in the region and that in the current census tract to the same highest tract-level pci.

**Development of Priority Indices**

The final step is to combine the exposure and social vulnerability of census tracts to develop the Priority Index. If the expected performance of utility service $K$ in census tract $m$ is denoted by $P_K^m$, then the weighted exposure in census tract, $E_m$ is given by Equation 10.

$$E_m = \sum_K (1 - P_K^m) \times w_K^m : 0 \leq E_m \leq 1, \tag{10}$$

where $w_K^m$ is the weight for utility service $K$ in census tract $m$. PI of a census tract for a given disruptive event, $PI_m$, is defined as the product of weighted exposure ($E_m$), and normalized social vulnerability index ($mSVI_{m,norm}$) corresponding to $m$.

$$PI_m = E_m \times mSVI_{m,norm} : 0 \leq PI_m \leq 1 \tag{11}$$

If a census tract has high social vulnerability and high exposure to the event, the PI will be close to 1. Conversely, if the census tract has low social vulnerability and is subjected to low exposure, the PI will be close to 0. Thus, the PI could be used to identify those census tracts that require immediate attention after a hazard occurs in the infrastructure network. This would help in making decisions that ensure rational utilization of available resources during emergencies.

# CASE STUDY

## Description of Infrastructure Network

The city of Austin, Texas is chosen for the case study. Since the primary goal of the paper is to demonstrate how urban areas can be prioritized for immediate relief operations for utility service disruptions during a hazard or an event, the authors created a semi-realistic network by limiting the number of utility services and adopting certain assumptions where actual data was not available. The infrastructure systems chosen for the study are power plants, substations, electricity maintenance service, water treatment plants, and sewage treatment plants. The location details of the infrastructure nodes are obtained from public data and reports published by the City of Austin (*19, 20*), and are presented in Figure 2. For simplicity of the network, it is assumed that each of the infrastructure unit has a unique service area, which do not overlap with each other. The details regarding the service areas of the water treatment plants and the sewage treatment plants, as well as the electrical maintenance service stations, are obtained from respective utility websites and official reports published by City of Austin. For those infrastructure systems such as substations and power plants (for which the service area details are not available), the service area is decided by the distance criterion, *i.e.*, all other utilities and buildings under study depend on the nearest substation and every substation depends on nearest power plant for its functioning. In addition to the locations of infrastructure nodes and their respective service areas, information regarding dependencies is also required for simulating the indirect impacts of the disruptive event on the network. Since this information was not available, appropriate values are assumed and are presented in Table 2. The values represent the reduction in performance at the 'consumer' node if the 'producer' node, which it is dependent on, is completely failed. For example, it is assumed that when a power plant fails, the the expected performance of dependent substations reduces by 90 percent.

**TABLE 2**: **Assumed Dependencies among Infrastructure Systems for the Case Study**

| **Producer/ Service Provider** | **Consumer** | | | | | |
|---|---|---|---|---|---|---|
| | Substation | Electrical Maintenance | Hospital | Power Plant | Water Supply | Sewage Disposal |
| Substation | 0 | 0.3 | 0.4 | 0.05 | 0.5 | 0.5 |
| Electrical Maintenance | 0.1 | 0 | 0.1 | 0.1 | 0.1 | 0.1 |
| Hospital | 0.05 | 0.05 | 0 | 0.05 | 0.05 | 0.05 |
| Power Plant | 0.9 | 0 | 0 | 0 | 0 | 0 |
| Water Supply | 0.1 | 0.3 | 0.3 | 0.05 | 0 | 0.3 |
| Sewage Disposal | 0.1 | 0.2 | 0.3 | 0.05 | 0.2 | 0 |

## Simulation Results

As discussed earlier in the paper, agent-based modeling approach is used to simulate the propagation of cascading and interdependent effect on the infrastructure network. To demonstrate this, an artificial disruptive event is generated which caused a water treatment plant to stop functioning entirely as shown in Figure 2 (denoted by dotted red rectangle). It is assumed that all the infrastructure nodes in the network function at maximum performance level prior to the event. The Anylogic® software package (*21*) is used to construct the infrastructure network model and simulate the impact of the event on the network. A step size of 1 minute is used for the simulation.

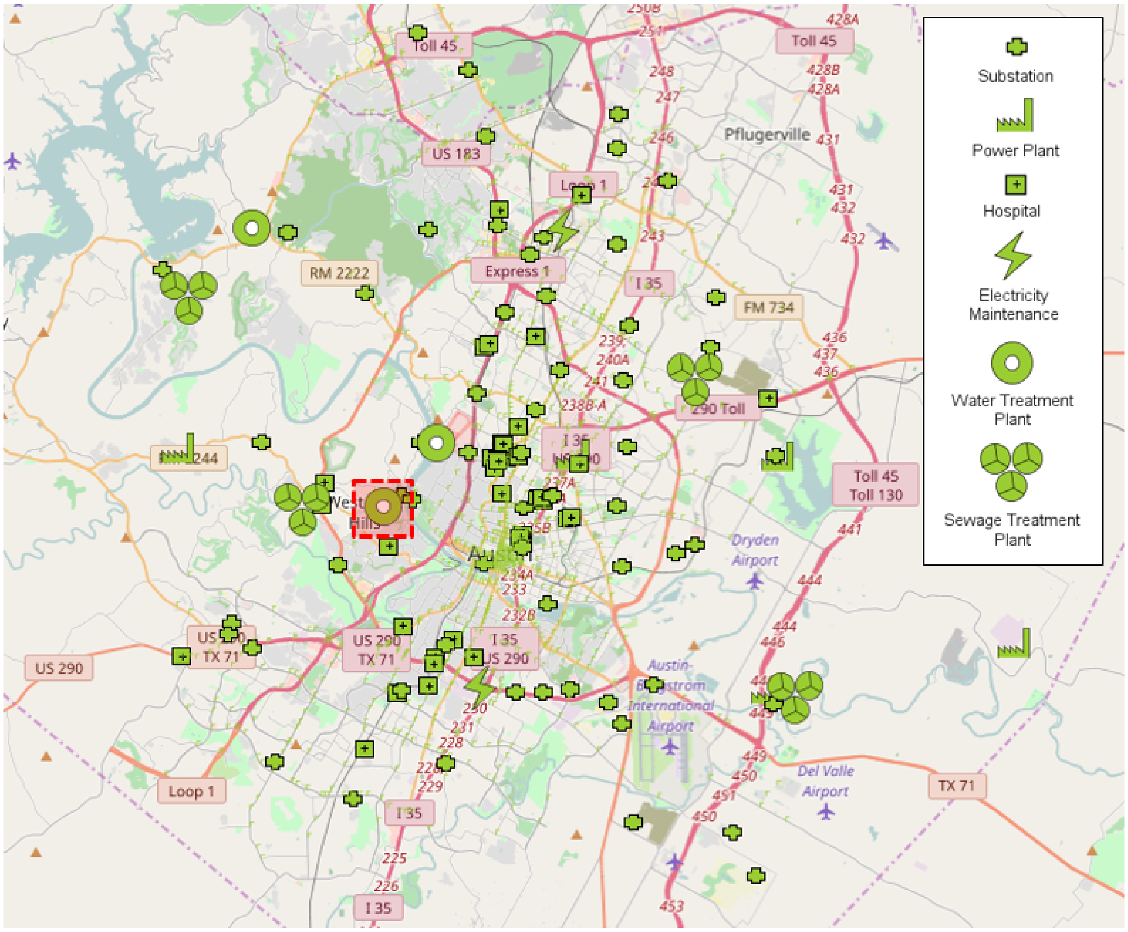


**FIGURE 2**: **Semi-realistic Infrastructure Network and Location of the Disruptive Event**

Figure 3 presents the simulated progression of expected system performance of various utility services after the disruptive event is generated. The failure of the water treatment due to the initial event is reflected in the expected performance of utility services such as healthcare, electricity, and sewage disposal, due to the existing interdependencies in the network. As it can be seen in the figure, the initial reductions in expected performance (lower order) in all utility systems are abrupt compared to the subsequent reductions. The initial reductions result from the direct and cascading impacts caused by dependencies. The comparatively smaller and higher order reductions in expected performance in the later stages could be attributed to indirect and interdependent effects. Once the higher order effects become negligible, the affected utility systems stabilize and attain new equilibrium, but with reduced performance levels. The expected performance of utility service nodes would remain the same until recovery activities are initiated to restore the water treatment plant.

Figure 4 provides the probability distributions of the reduced expected performance of various utility service nodes once the network stabilizes after the event. The electricity supply in various census tracts after the event ranges from 35 percent to 92 percent with an average of 70 percent (Figure 4a). Similarly, the performance of hospitals ranges from 28 percent to 87 percent with an average of 52 percent (Figure 4b). The performance of water supply service ranges between

0 percent and 84 percent with average of 54 percent (Figure 4c), and that of sewage treatment service ranges between 39 percent and 89 percent with average of 45 percent (Figure 4d).

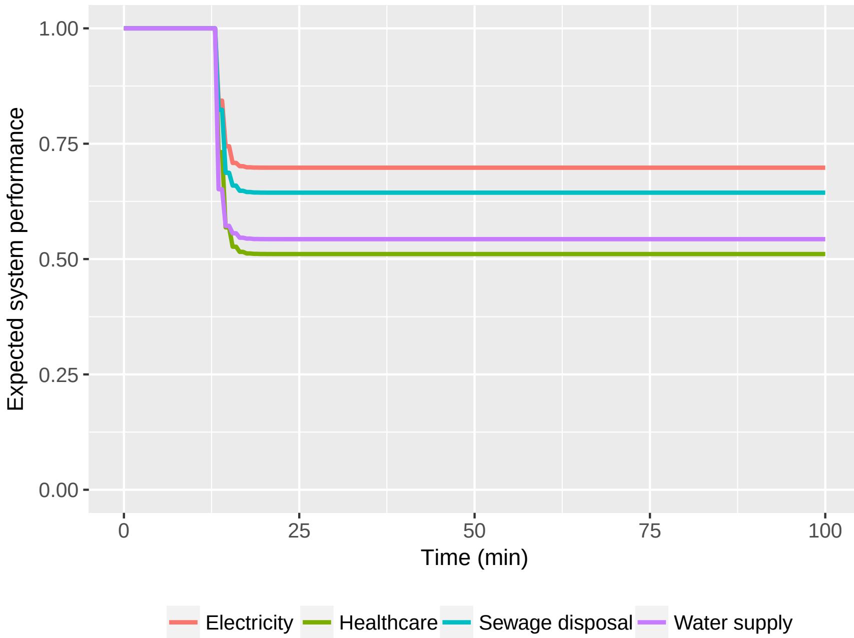


**FIGURE 3**: **Simulated Impact of the Disruptive Event on the Expected Performance of Infrastructure Network (Cascading and Interdependent Effects Combined)**

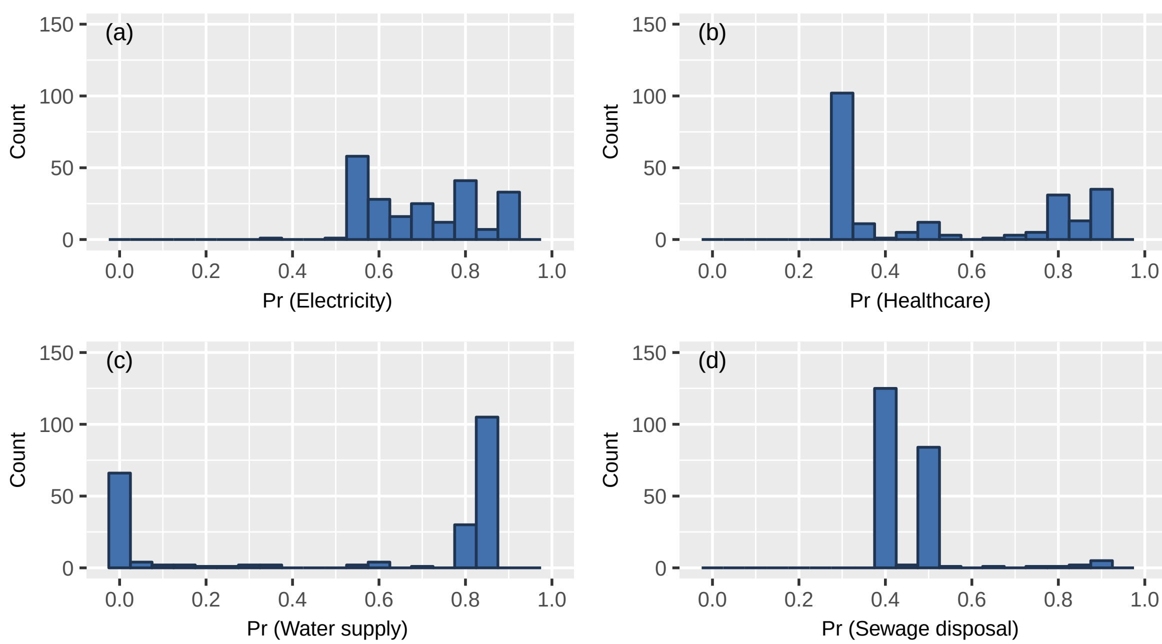


**FIGURE 4**: **Distribution of Public Utility Disruptions in Census Tracts under Consideration: (a) Electricity; (b) Healthcare; (c) Water Supply; and (d) Sewage Disposal**

Though Figures 3 and 4 provide an overall idea about the post-event expected network performance (and probability of failure), this is of insignificant use from a decision maker's perspective unless the spatial distributions of the expected performance loss of utility services are understood. For this purpose, a random sample of 10,925 buildings (approximately 2% of total building footprint) distributed in the study area is selected. The buildings are then classified according to the respective utility nodes they depend on for their functioning (electricity, healthcare, water supply, and sewage treatment), and corresponding performance levels are identified. The buildings are then mapped to the census tracts to which they belong. In this way, the distribution of utility disruptions in all the 222 census tracts under study are obtained. The expected levels of utility disruptions in each of the census tract are presented in Figure 5. Figure 5a shows the

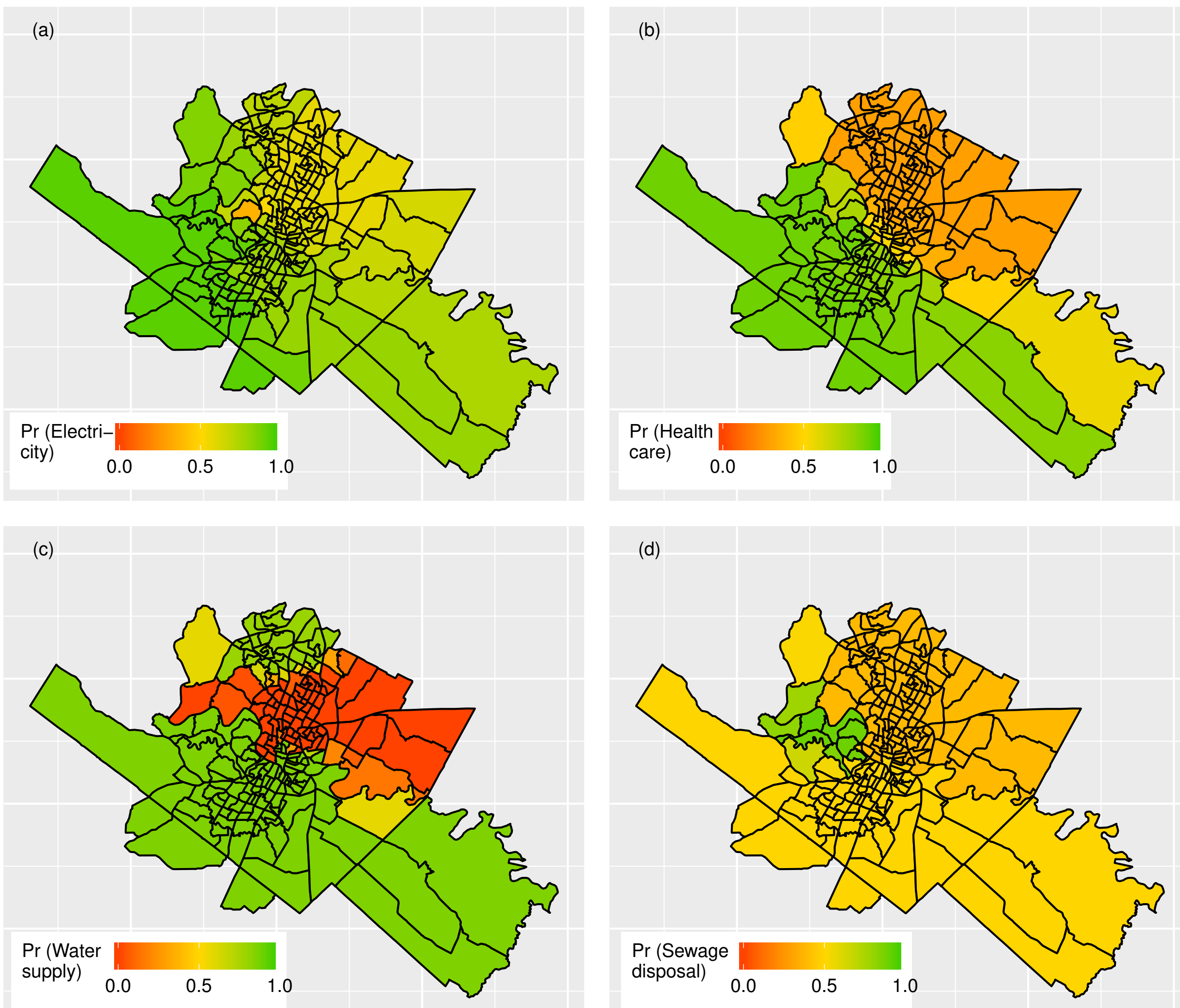


**FIGURE 5**: **Spatial Distribution of Utility Disruptions Based on Census Tracts: (a) Electricity; (b) Healthcare; (c) Water Supply; and (d) Sewage Disposal**

levels of electricity supply in the study area after the occurrence of the event. It can be observed that electricity supply disruptions are more likely to occur in census tracts in the northeastern and southeastern parts of Austin as shown in Figure 2. Similarly, Figure 5b shows that the functioning

of hospitals in the north and northeastern parts are more likely to be disrupted. This suggests that a significant fraction of the communities will have access to no or less efficient healthcare. In addition, Figures 5c and 5d illustrate how the failure of the water treatment plant could affect the water supply and sewage treatment services in different parts of the city, respectively.

**Estimation of Weighted Exposure and Social Vulnerability**

Analyzing the spatial distribution of the performance of utility services, it is evident that the degree of utility disruptions differs significantly across census tracts. For example, in the northeastern parts of the city, the simulation results predict that there will be almost no water supply and considerable reduction in the performance of healthcare and sewage disposal services. However, in the census tracts in the southwest, the probability of disruptions in sewage disposal service is high, whereas, other utility services are expected to function satisfactorily. To identify the most affected census tracts due to the disruption in utility services, a weighted performance measure is calculated. In reality, the dependency of buildings and communities on utility services differ from one region to another, depending on socio-economic factors. In such scenarios, it is possible for the decision maker to provide actual weights for the utilities to obtain the weighted exposure on the urban region. For this case study, the weighted exposure is obtained by assuming a weight factor of 0.25 for all the four utility services. The weighted exposure values of census tracts are presented in Figure 6a.

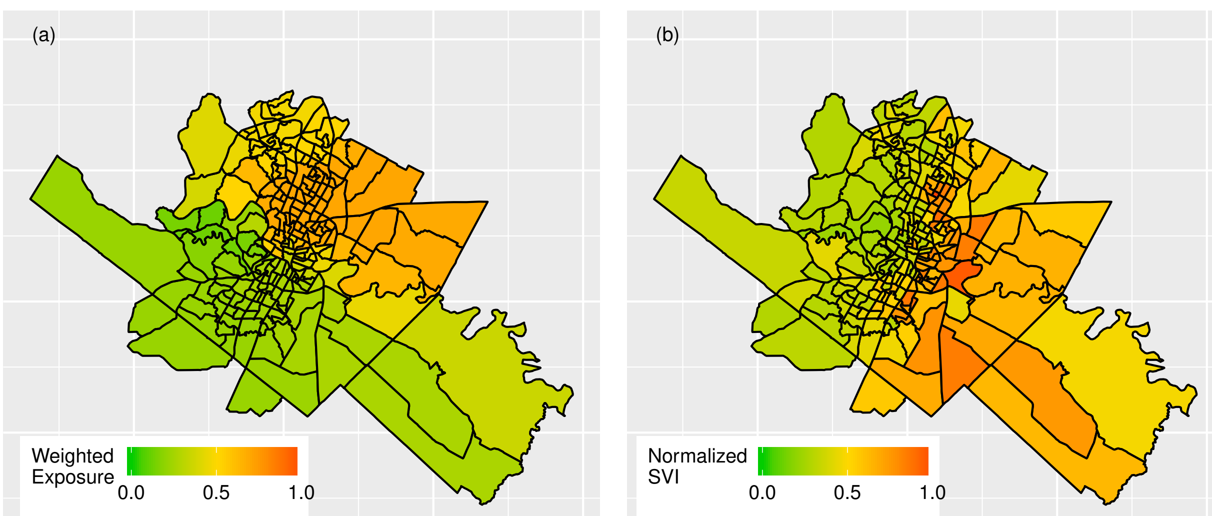


**FIGURE 6**: **(a) Normalized mSVI Values of Census Tracts Under Study; (b) Weighted Exposure of the Combined Effect of the Disruptive Event on Communities**

In addition to the geographical distribution of exposure to the disruptive event, it is also important to analyze the generic socio-economic, demographic, and housing characteristics of the census tracts. To estimate the vulnerability of the communities, normalized social vulnerability indices ($\text{mSVI}_{\text{norm}}$) of census tracts were computed from the 2014 ACS data, based on the methodology explained in the methodology section. The $\text{mSVI}_{\text{norm}}$ values are presented in Figure 6b. The results show that the communities residing in the eastern part of the city are comparatively more vulnerable to disasters and service disruptions than those in the western part. This can be directly

linked to the socio-economic disparities existing between the communities residing in the eastern and western sides of Interstate-35, which runs north-south of Austin.

**Calculation of Priority Index**

The Priority Indices for the census tracts are calculated using Equation 11. The results are presented in Figure 7. The results show that the northeastern regions of the city have high index values, indicating that those regions are more likely to be affected by the given water treatment plant failure. Communities in the southwestern region are the least likely to be affected by the same hazard. More importantly, it is possible from the figure to easily identify the census tracts that require immediate attention, and those do not. This property of PI makes it an easy and efficient tool for managing utility disruptions.

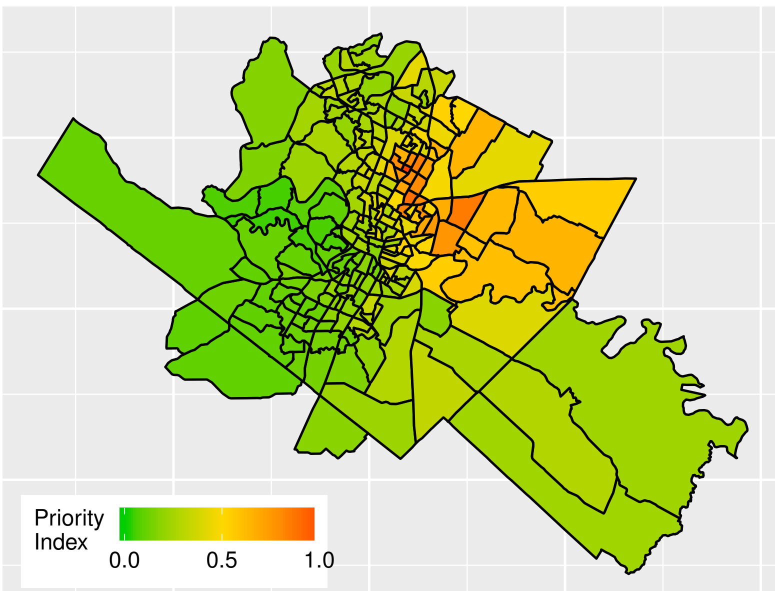


**FIGURE 7**: **Priority Index Values of Census Tracts Under Study for the Generated Disruptive Event (PI = 1: Highly Susceptible; PI = 0: Not Susceptible)**

**CONCLUSION**

In the present study, a ratio-scale measure, Priority Index (PI), is proposed to evaluate the susceptibility of communities to unanticipated events and the resultant utility disruptions. The advantage of PI is that it is equally dependent on the generic social vulnerability of communities, as well as the degree of exposure to a given disruption on the network, enabling it to reflect the real conditions of communities in various parts of the urban region during utility disruptions and hazards. In addition, it enables comparison of susceptibility of two census tracts using a linear scale. The performance drop in the infrastructure network is evaluated by giving due consideration to both the direct and indirect impacts of hazards arising from its interdependent structure.

The framework could be employed for emergency planning and disaster risk assessment, as well as for managing immediate relief operations, such as distribution of food, and water during a disaster. The framework could find potential applications in cities where backup mechanisms to

withstand prolonged and uncertain utility service disruptions are unreliable or absent. The results from the study underscore the importance of proper management of interdependent infrastructure systems to ensure the well-being of urban communities.

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